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Directed Study - Accounting
Boston University, June 2019
Revised November 2019

Does Financial Statement Analysis help pick winners from an OTC equity market?

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1. Notes About this Paper

This paper was written, from conception to this draft, in a seven-week span in the summer of 2019 for a directed study for Francois Brochet (Boston University, Associate Professor of Accounting) during my MBA. After only one half-semester in Washington University's DBA in Finance program, there are many things I would change about this study to improve upon it. These improvements include but are not limited to

- I should've used more literature to set up problem and define why OTC asset pricing is academically interesting. Papers like Hou et al (2015), Fama and French (1996), discussions of the FF-3 and FF-5 models, and even statistical methods like the GRS from Gibbons, Ross, and Shanken (1989) should've been the backdrop for this discussion.
- This study suffers from lookahead and survivorship bias as I weeded out companies that didn't have five full years of price data and one wouldn't know which companies would have had five full years of price data at t = 0. One could (correctly) infer that I choose companies at t = 0 that would have a good chance at surviving for five years in the OTC market which undermines the entire study.
- Using API-pulled CRSP/COMPUSTAT data via interfaces like WRDS would increase the time horizon studied which would improve the representability of statistical results. There was a lot of manual computation involved with Piotroski F-Score which I can now automate which is why I only performed the analysis over 5 years.

- Using different regression techniques (ones not only AR in nature) would help explain, as well as potentially predict, FSA impact on equity returns. I reported the FE OLS results in a table so readers can easily understand the values of the factors uncovered and their statistical significance but could've done this with other tangential questions to make the analysis more rigorous.

I am continuing to explore the issue of fundamental factors on security selection. This fall, I will be using CRSP/COMPUSTAT data over a longer time series (possibly 1980-2018) to construct (possibly decile) portfolios on B/M and size to apply the (possibly modified) F-Score to determine the differences in returns across those portfolios. The regression analysis will be much simpler in design yet more concise as I aim to simply explain the power of fundamental analysis on these micro-cap securities. This analysis will be taking place in Guofu Zhou's "Data Analysis for Investments" class in the Olin Business School at Washington University in St. Louis as part of my DBA program. If you have any questions about this paper or the topic in general, please feel free to reach out to me at dbaines@wustl.edu.

2. Abstract

While there is literature pertaining to the validity of value-accretive firm selection strategies utilizing financial statement analysis (FSA) in equity markets (Graham and Dodd, 2008; Piotroski, 2002), this study aims to test whether FSA can be effectively applied in over-the-counter (OTC) equity markets to pick "winners" - firms that achieve statistically significant positive returns over firms that do not pass an FSA test – from that market. OTC equity markets are unique in that they contain companies with smaller market valuations than exchange-traded firms and, if healthy companies can be found within, their lower market equity values when

compared to exchange-traded firms should mean higher per-share returns as shown by many authors, most famously Eugene Fama and Ken French. Since most firms in OTC markets are in a state of distress, applying FSA to identify the “winners” from the “losers”, or firms that don’t pass an FSA test, is critical. Using Piotroski’s F-Score on US-based firms in the OTCQX market, I find that the use of this particular FSA selection test does generate statistically significant positive returns the five-year period analyzed (2014 to 2018) when certain definitions of “winner” are used but not with other definitions. I also find that market conditions of the OTCQX market as well as the overall performance of small-cap firms satisfactorily explain the returns of firms in the OTCQX at all definitions tested. The general market as represented by the S&P 500 does an adequate job at explaining OTCQX firm return with certain definitions of firm health but not with others. Factors of liquidity, information, other exogenous market factors, and company health not captured in Piotroski’s F-Score could be even more effective in explaining returns in the OTCQX but more research must be conducted to validate this claim.

3. Objectives

Inspired by Warren Buffett’s application of the “intrinsic value” stocking-picking technique articulated by David Dodd and Benjamin Graham in their 1934 work “Security Analysis”, my intention with this study was to determine if a formulaic approach of value assessment could be applied to contemporary OTC equity markets. Buffet’s “intrinsic value” approach entails buying stocks whose market price is trading below the respective firm’s per-share net asset value. While Buffett used this approach when picking investment-grade securities from the Moody’s Pink Sheets in the 1950s and 1960s (Schroeder, 2009), the US equity markets were far less complicated then than they are now. As an example, an investor in the 1950s could not rely on the Internet for real-time price quotes thus securities would remain “mis-priced” for long amounts of time. This lack of information in the market allowed the few investors willing to read

SEC filings to find attractive value investments before the market caught on and corrected the security's price. Today, information asymmetry - and consequently equity spreads - are reduced since investors can obtain a firm's financial reports online without having to acquire such documentation through the SEC's physical office before placing a trade. Online pricing information allows investors to determine a firm's market valuation in real-time, even in OTC markets where, in the pre-Internet era, a buyer and seller would negotiate between themselves the appropriate price for the stock.

With this context, the objective of this study was to determine if applying an objective and formulaic FSA framework to a market of OTC, small-cap companies yields higher investment returns relative to not using FSA for a selection test. Using Piotroski's F-Score, 50 companies from the OTCQX market were examined from 2014 to 2018 and, if a company passed the F-Score test, it was deemed a sound investment, or "winner", for the following year. The returns of the "winners" were then tracked against the S&P 500 return, the overall OTCQX market return, and the returns of the firms that did not pass the F-Score test, defined as "losers". The "winner" portfolio was rebalanced every year to account for changes in company health over the five reporting periods. The results show that, while there is a statistically significant relationship between the application of FSA as a selection test on these firms and their returns in the following year, the economic significance is marginal. The data used in the study, the methodology and assumptions used in the analysis, and the interpretation of the findings are outlined below.

4. Data

4.1. Overview

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The OTC Markets Group facilitates the purchase and sale of small-cap equity securities in the US and beyond. They have four tiers of markets for their securities - Grey, Pink, OTCQB, and OTCQX - which represent varying stages of disclosure, equity values, status of distress (if any), and general health of the firm. The Grey, Pink, and even OTCQB markets contain firms with incomplete financials or non-current disclosure making financial research ungeneralizable. The market with the highest quality information, and most stringent standards of disclosure is the OTCQX market[1]. Of these 465 firms, 154 of them are based in the US which was an important attribute since returns of these firms were intended to be compared to US benchmarks like the S&P 500 and the Fama-French “SMB” factor (Fama, French, Booth & Sinquefield, 1993). Of these 154 companies, 89 had five years of complete financials and daily price data which was necessary to represent the overall OTCQX market performance. From this pool of 89, 50 firms were selected at random for the sample of companies used in the regression equation described in Section 4.2.

To accurately calculate stock returns for the selected companies in the sample (n = 50) and the overall market (n = 89), the five-year daily price data was taken from Yahoo Finance as it was adjusted for dividends and splits. Given the high equity volatility in the OTCQX market by its (typically) unhealthy participants and the steady stream of dividends by its healthy ones, using adjusted closing prices that accounted for these changes in equity made a like-for-like comparison possible. Financial statement information used in the calculation of the F-Score was taken from the Mergent Online database.

To determine if the overall performance of small firms helps explain OTCQX firm performance, I used the Fama-French “SMB” factor with data taken from Kenneth French’s

[1] https://www.otcmarkets.com/corporate-services/get-started/otcqx-us, retrieved June 23rd, 2019

website[2]. These yearly SMB factors were used in the panel data set to correspond to the periods for which they represent.

Finally, a general market factor was created to help explain OTCQX firm performance. To serve as a proxy for the condition of general equity market, annual returns of the S&P 500 were used. Yearly returns were calculated from S&P 500 Index prices taken from the Federal Reserve Bank of St. Louis' "FRED" website[3].

4.2. Adjustments

Of the 50 companies used in the analysis, 22 of them (44%) were banks. For the non-bank companies, traditional items in the statements like revenue, cost of goods sold (COGS), and current assets and liabilities can be used for determining the ratios needed in the Piotroski F-Score. These include return on assets (ROA), leverage, and operating accruals. For the companies that operated as banks, the following definitions were established.

- Revenue was defined as total interest income for the period
- COGS was defined as total interest expense for the period
- Long-term debt was defined as the amount of total long term borrowings reported at the end of the period which can include notes, debentures, advances, and traditional long-term debt
- Current assets were defined as the current amount net loans reported at the end of the period
- Current liabilities were defined as the current amount of deposits reported at the end of the period

[2] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research Retrieved June 24th, 2019.
[3] https://fred.stlouisfed.org/series/SP500. Retrieved June 24th, 2019.

5. Methodology

5.1. Data Preparation

The Piotroski F-Score utilizes items from all three financial statements to determine a score for the firm's health on a scale of 0-9, with healthy companies receiving a higher score. This score is designed to rate three areas of a company's health: profitability, financial leverage, and operating efficiency. While proprietary frameworks were considered for examining firm health (trends in EBITDA or debt-free cash flows, for example), the Piotroski F-Score is more comprehensive as it encompasses leverage and operating efficiency along with profitability. The framework is also formulaic and easily applicable; it has been shown to select "winners" and "losers" from equity markets albeit only in exchange-traded markets[4].

As explained in Piotroski, 2002, the points are defined below.

Profitability

- Return on Assets (1 point if it is positive in the current year, 0 otherwise);
- Operating Cash Flow (1 point if it is positive in the current year, 0 otherwise);
- Change in Return of Assets (ROA) (1 point if ROA is higher in the current year compared to the previous one, 0 otherwise);
- Accruals (1 point if Operating Cash Flow/Total Assets is higher than ROA in the current year, 0 otherwise);

Leverage, Liquidity and Source of Funds

- Change in Leverage (long-term) ratio (1 point if the ratio is lower this year compared to the previous one, 0 otherwise);

[4] Piotroski, 2002. Page 16.

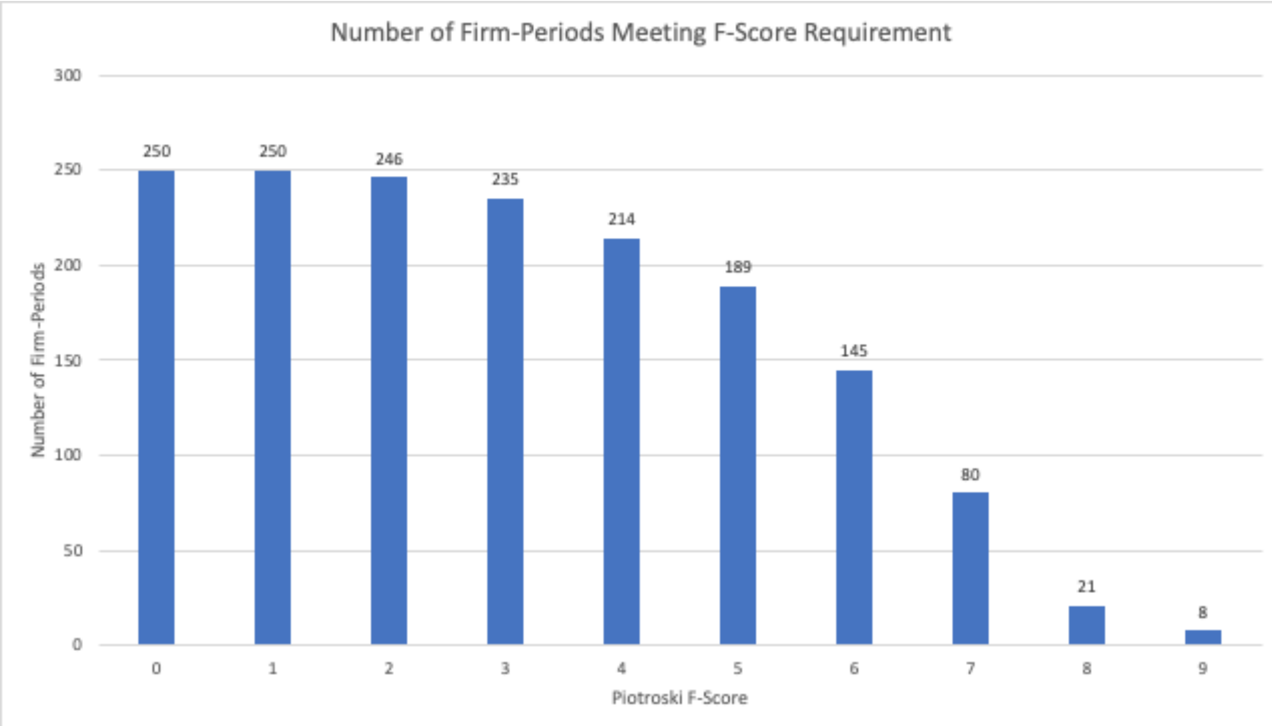
- Change in Current ratio (1 point if it is higher in the current year compared to the previous one, 0 otherwise);
- Change in the number of shares (1 point if no new shares were issued during the last year);

Operating Efficiency

- Change in Gross Margin (1 point if it is higher in the current year compared to the previous one, 0 otherwise);
- Change in Asset Turnover ratio (1 point if it is higher in the current year compared to the previous one, 0 otherwise);

With the framework selected, the three financial statements of each of the 50 OTC companies in the sample were inspected and scored according to the F-Score methodology for each year - 2014 to 2018 - in the study. In all, 250 F-Scores were calculated. Since a higher score indicates a healthier company, a derivative score, called the D-Score, was created to indicate whether the company met a minimum F-Score requirement for the period. The D-Score is a binary variable that equals 1 if the firm-period meets the minimum F-Score requirement and 0 if it does not. If the D-Score was equal to 1, the firm was "purchased" for the "winner" portfolio and was not purchased if the D-Score equaled 0. **CHART A** shows the cumulative distribution of firm-periods for each score in the F-Score scale for all five periods.

CHART A - Cumulative Distribution of Firm-Periods that Pass Given F-Scores



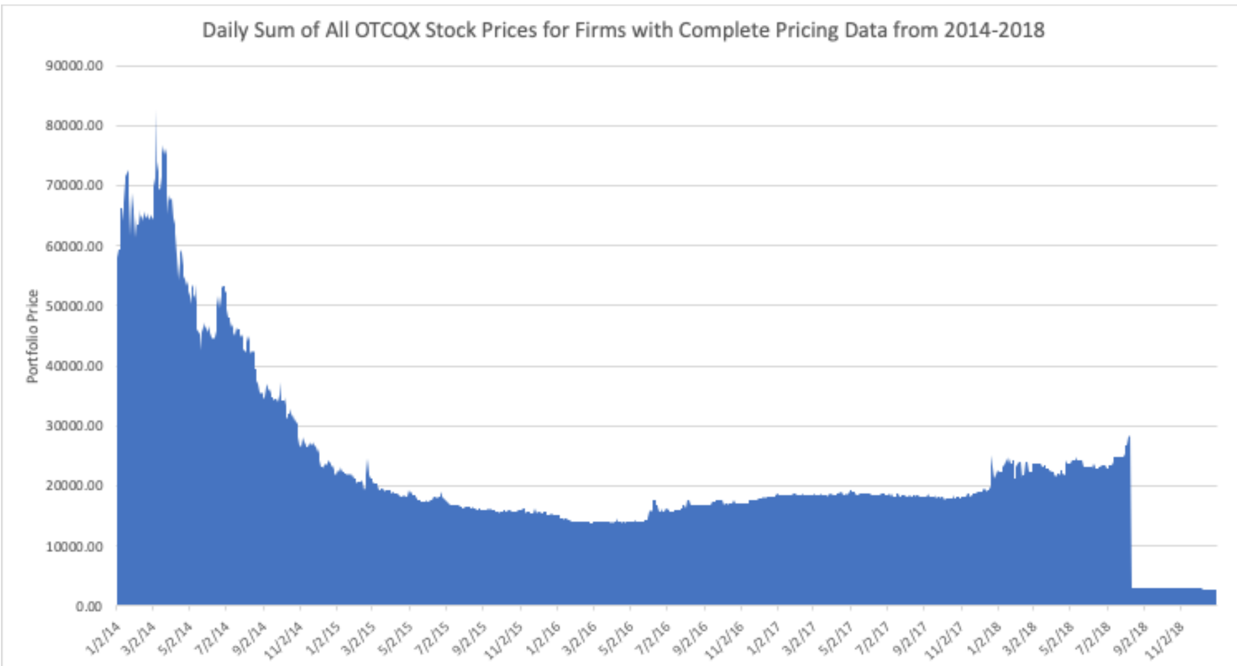
According to Piotroski, an F-Score of 8 or 9 signifies a "winner" in his 14,043-firm[5] sample. I decided that a score of 7 or above signifies a "winner" in the OTC market given two factors: the destruction of value in the overall OTCQX market over time (**CHART B** depicts the total OTCQX market value for firms persistent across all five periods from 2014 to 2018) and the exemption of the "Equity Offer" factor as Poitroski punishes firms for share buybacks.

The rationale for this latter assumption is that a healthy company could buy its undervalued shares back to increase equity which theoretically raises its stock price. However, due to a lack of analyst coverage in the OTCQX market, this action would go unnoticed and the price would not be corrected by the market. While the value of shares changes in this transaction, I do not believe that a score of 0 for this F-Score factor is accurate since healthy companies decrease outstanding shares by using cash to increase book equity. Because

[5] Piotroski, 2002. Page 15

Piotroski cites an increase in shares as a possible funding source and thus liquidity warning sign yet does not account for a decrease in shares for buybacks, I believe the “Equity Offer” factor in the F-Score should be omitted.

CHART B - Daily Market Value of OTCQX Market



For the sake of rigor, I have included regressions for minimal F-Scores of 6, 7, and 8 which are represented by varying definitions of the $DSCORE$ binary variable in the regression equation in Section 4.2 and its output in Section 4.3.

5.2. Regression Design

With the data in panel form and ready for analysis, a fixed-effects regression (with entity demeaned group intercepts and cross-section weighting to allow for per-firm heteroskedasticity) was run on the panel to determine the effects of four factors on OTCQX firm yearly performance. The regression equation used was

$$Return_{it} = \alpha_i \; + \; \beta_1 DSCORE_{it-1} + \beta_2 OTCQX_t + \beta_3 MARKET_t + \beta_4 SMB_t + \mu_{it}$$

where

- $Return_{it}$ is the predicted return of firm *i* in year *t*,
- α_i is the firm-specific intercept (explained in more detail below),
- $DSCORE_{it-1}$is the last period's D-Score for firm *i*,
- $OTCQX_t$is the current year's OTCQX overall return,
- $MARKET_t$is the overall market as represented by the S&P 500 return in year *t*,
- $SMB_t$is the Fama-French SMB factor in yearly form, and
- $\mu_{it}$is the error term for firm *i* in year *t*.

The fixed effects model (FEM) was used for this regression in an attempt to keep constant any firm-specific attributes that could affect performance over the 5-year period such as management; market trends; industry-specific features like margin, cash flow, or capital structure; or other firm-specific factors that affect their yearly returns. The per-firm intercept $\alpha_i$attempts to capture this linear effect. With only five years of data (four years if the year-long lag for D-Score is included), this approach is consistent with accurate statistical results. However, a study with longer time horizons such as Piotroski's 20-year returns for finding coefficients for his F-Score may find value using a random effects model (REM) as this could approach may determine if per-firm intercepts are non-linear.

$DSCORE_{it-1}$ attempts to capture the effect of a passing or failing D-Score for firm *i* in the period *t - 1*. As a reminder, the D-Score is the binary variable that represents if firm *i* obtained the minimum passable F-Score in year *t*. The assumption is that an investor would perform the F-Score analysis in year *t - 1* and, based on their requirement for defining a company as a "winner" (F-Scores of 6, 7, and 8 were captured in this study), they would either buy or pass on the security in year *t*. This purchase of the security is captured by a D-Score of 1. The portfolio of purchased securities is rebalanced every year. Transaction costs are ignored in per-year returns and it is assumed that investors have all available information in year *t - 1* to make a purchase decision for year *i*.

$MARKET_t$ is a factor intended to capture the general condition of the overall equity market. While OTC stocks have two main attributes that could cause conceptual deviation from the general market's movement - first, information asymmetry due to low trading volume and a lack of analyst coverage and, second, the general destruction of overall value in the time horizon studied as depicted in **CHART B** - my intent was to capture unknown yet correlated factors of the general market to help explain OTCQX firm performance. Examples would include tax effects, cost of borrowing, and general economic production.

$OTCQX_t$ attempts to capture the unique, intrinsic forces of the OTCQX market in year *t* on OTCQX firm *i*. As described above, the factor is intended to encapsulate effects pertaining to a lack of analyst coverage and a general destruction of market value (due to financial health concerns, delistment, shrinking business prospects, etc) but this factor could represent other market forces as well. A further dissection of this factor to find sub-factors that better explain firm performance should be undertaken in further study of this issue. Given the positive correlation between average firm performance and the contemporaneous return of the market in which its sits, it follows that it is statistically significant at every reasonable level in the three regressions that were run.

SMB_t is the Fama-French SMB factor for year t. This factor is designed to help explain the general performance of smaller companies (as is the case of all firms in the OTCQX market) against larger ones such as those in the S&P 500. Attributes of this factor can include items such as fluctuations of equity on a per-dollar basis given their comparatively small values and its causal impact on small-cap stock price.

Finally, μ_{it} is the model error term that captures every other factor that explains firm *i*'s performance in year *t.* By definition, it is unknown what those factors are, but, given the statistically adequate yet conceptually moderate R^2 and $\overline{R^2}$ of the models used in Section 4.3 to describe firm returns given the independent factors included, further exploration to understand these factors would need to be endeavored to improve the fit and forecasting accuracy of the model. The model created includes mostly contemporaneous factors therefore factors that help predict performance instead of explain it would be helpful in further studies.

5.3. Results and Interpretation

The regression designed above was run across the five-year period from 2014 to 2018 with 2014 being used as the lag for the $DSCORE$ variable. The regression was run under three different $DSCORE$ definitions to determine if changing the minimum F-Score required to result in a "passing" D-Score made any difference to the explanation of firm performance. **TABLE A** displays the intercepts, coefficients, errors, and model fit measures (R^2 and $\overline{R^2}$) for those three scenarios.

TABLE A - Output of Fixed Effects Regressions on Firm Yearly Return

Minimum F-Score 6

Variable	INTERCEPT	OTCQX	SMB	MARKET	DSCORE(t - 1)
Coefficient	0.1652	0.3115	-1.0605	-0.3115	0.0603
Standard Error	0.0259	0.0537	0.2519	0.2229	0.0287
T-Stat	6.3794	5.8053	-4.2099	-1.3972	2.1036
p-value	0.0000	0.0000	0.0000	0.1645	0.0371
R^2 (with weighting)	0.8432				
Adjusted R^2	0.7862				
n with D-Score of 1	145				

Minimum F-Score 7

Variable	INTERCEPT	OTCQX	SMB	MARKET	DSCORE(t - 1)
Coefficient	0.2222	0.3996	-0.7137	-0.7088	0.0469
Standard Error	0.0233	0.0650	0.2819	0.2790	0.0222
T-Stat	9.5278	6.1524	-0.2532	-2.5402	2.1121
p-value	0.0000	0.0000	0.0124	0.0121	0.0364
R^2 (with weighting)	0.8589				
Adjusted R^2	0.8076				
n with D-Score of 1	80				

Minimum F-Score 8

Variable	INTERCEPT	OTCQX	SMB	MARKET	DSCORE(t - 1)
Coefficient	0.1930	0.3010	-1.0203	-0.3062	0.0371
Standard Error	0.0223	0.0525	0.2471	0.2199	0.0438
T-Stat	8.6778	5.7286	-4.1288	-1.3920	0.8465
p-value	0.0000	0.0000	0.0001	0.1660	0.3987
R^2 (with weighting)	0.8404				
Adjusted R^2	0.7824				
n with D-Score of 1	21				

The results indicate that there is a statistically significant effect of the previous year's $DSCORE$ on a firm's annual return when the minimum F-Score required to define a "winner" is 6 or 7, but not when the F-Score to define a "winner" is 8. This aligns with the fact that there are only 21 firm-periods with an F-Score of 8 or higher which could (and does) yield a high SE for that factor. Using the hypothesis that a "winner" in the OTCQX market would have an F-Score of 7 or higher, an investor could expect a 4.69% increase in returns over firms that do not achieve a score of 7 or higher. However, it is important to note that the OTCQX market has an average annual return of -27.67% for the period lasting 2014 to 2018 (calculated from the aggregate of stock prices for firms that have reported financials and daily price information from Jan 2nd, 2014 to Dec 31st, 2018) indicating that firms that pass this selection test would only see less negative returns. This attribute is also demonstrated by the negative value of the $MARKET$ coefficient (although not statistically significant in two cases) and the positive and statistically significant $OTCQX$ coefficient.

The conclusion of the test is that the coefficients in the model are statistically significant in certain conditions but not in others. No condition is economically significant as more (or potentially different) factors would have to be included to determine how an investor could pick a "winner" from the OTCQX market in the future while using data from the past. In other words, because of the general destruction of the OTCQX market over the time horizon studied, even though statistically significant, this model wouldn't be used in practice as the risk-free rate or even a lack of investment activity (return of 0%) would be a better investment alternative than picking "winners" in the OTCQX.

5.4. Model Diagnostics

5.4.1. Fit

The R^2 and $\overline{R^2}$ for the three definitions of $DSCORE$ with weighted cross section errors (to allow for per-firm heteroskedasticity) are presented in **TABLE A**. On a weighted basis, the model explains 84.04% to 85.89% of the variance in firm *i*'s annual return in year *t* (with the D-Score definition of a passing F-Score being 7 or higher). This finding aligns with the fact that three of the independent variables in the regression - overall market performance (which encapsulates items such as cost of borrowing, general economic climate, and tax effects), OTCQX market performance, and the general performance of small-cap securities - are logically connected to the return of the firm in the dependent variable, especially when noted that these factors are occurring in the same period (contemporaneous correlation). Even with a relatively high R^2 and $\overline{R^2}$, I would like to further study this problem to determine which factors yield a positive return as the factors in this model, while statistically well fit, do not tell us much about predicting future stock performance in the OTC market with information from previous periods.

5.4.2. Autocorrelation and stochasticity

Due to the short time horizon of the panel data (5 years with a year of lag for the $DSCORE$ variable), tests for both autocorrelation (with the Durbin-Watson test) and stochasticity (Dickey-Fuller test) are not valuable. The Durbin-Watson outputs for the regressions imply a slight positive correlation (~2.5) but this indicator is of little value as there are only five periods.

5.4.3. Errors

I used cross section-weighted errors in the regression as they correct for heteroskedasticity in the firm dimension. Other correction techniques like period weights or SUR cannot be used since the cross sections (n = 50) outnumber the periods (n = 5) yet could be used in further study when the time horizon is expanded.

5.4.4. Forecast

Since the coefficients in the regression equations represent yearly values and the data used in the study ends in 2018, I am not able to forecast 2019 returns for OTCQX firms to test that forecast against actual 2019 results. To expand on the findings presented in this paper, I would like to build regression coefficients with a longer time horizon (20 years, for example) with shorter periods for t (months, for example) to forecast out five years on pseudo-out-of-sample data. With that methodology, I would have enough forecasted and actual data to compute statistically valuable root mean squared forecast errors (RSMFE) to determine the model's ability to accurately predict future performance.

As a proxy for a forecast from the regression equation, I have compiled YTD returns (ending June 25th, 2019) for firms in the OTCQX market pool (n = 89) that have scored at least a 7 on the F-Score scale for 2018 (n = 20). These returns where then compared to YTD returns (ending June 25th, 2019) of the S&P 500. This proxy aimed to test whether applying the D-Score test in year *t - 1* (2018) has produced positive returns in year *t* (2019) and by how much relative to a common benchmark (S&P 500). While a stylized forecast in the sense that 2018 financial information would not be available to investors until February or March of 2019 to influence their decision to purchase the stock, the forecast shows that firms who pass the 2018 F-Score test of a 7 or higher do in fact see positive returns for 2019 YTD (17.35% on average). These returns are higher than the S&P 500 YTD return of 16.23%. **TABLE B** presents these findings.

TABLE B - 2019 YTD Returns of OTCQX Firms with 2018 F-Score Above 6

Company	Closing Price 1/2/2019	Closing Price 6/25/2019	Return
MGHU	$17.40	$18.00	3.45%
CNIG	$18.50	$21.50	16.22%
OTCM	$29.12	$34.85	19.68%
REPR	$1.51	$2.95	95.36%
NOBH	$21.00	$22.50	7.14%
IEHC	$14.00	$17.00	21.43%
ONVC	$1.37	$2.80	104.38%
TYCB	$33.11	$34.80	5.10%
STBI	$19.80	$22.00	11.11%
MNAT	$32.00	$32.00	0.00%
FBAK	$263.00	$240.00	-8.75%
ENBP	$34.55	$39.90	15.48%
CBAF	$57.75	$56.50	-2.16%
KTYB	$22.70	$24.33	7.18%
BHWB	$26.60	$27.62	3.83%
CFNB	$14.15	$15.50	9.54%
BNCC	$20.90	$28.15	34.69%
DBIN	$36.00	$36.00	0.00%
ALRS	$19.95	$18.90	-5.26%
CHBH	$49.26	$53.50	8.61%
		Average Return	17.35%
S&P 500	$2,510.03	$2,917.38	16.23%

6. Summary

The intention of this study was to determine if using an objective and formulaic financial statement analysis (FSA) framework could help an investor choose “winners” in an OTC equity market. Inspired by Warren Buffett’s “intrinsic value” approach to security selection, I gathered data on companies in the OTCQX market and applied the Piotroski F-Score to firm over a five-year period.

With this data, I ran a series of fixed effects regressions to determine if the F-Score approach uncovered companies that yielded positive returns over companies which failed to pass a minimum F-Score requirement, captured by a binary variable called the D-Score. I found that the application of the F-Score does earn an investor positive returns over firms that do not pass the D-Score test over the time horizon tested, although the general destruction of value in the OTCQX market could mean negative returns in absolute terms when compared to general market behavior. A stylized forecast into 2019 using 2018 “winners” chosen using the F-Score technique does earn an investor positive absolute returns but the assumptions made in that forecast cloud its empirical validity; more periods would be needed to provide such validity.

While statistically significant and yet marginally economically significant under most conditions in this study, the application of the F-/D-Score requires further research as longer time horizons and an improvement in independent variable selection could help better explain OTC equity returns in future periods, not just contemporaneous ones. Factors pertaining to liquidity, information and coverage, events, and funding could be ones that yield further explanation of stock performance in period $t + 1$ in OTC markets and these should be explored in more detail. A longer time horizon would also help uncover any stochastic trends or autocorrelation in the data.

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